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We use the setup for Section 7 in Freedman and Berk (2008), with only one period. We have the unweighted world governed by π , and the weighted world governed by $\tilde{\pi}$. In the unweighted world,

- (i) subjects are IID,
- (ii) Z, V are independent,
- (iii) $\pi(X = 1|Z, V) = p(Z)$, where $0 < p(Z) < 1$ does not depend on V ,
- (iv) $Y = \Phi(X, Z, V)$, where Φ is a measurable function that does not depend on U ,
- (v) V is independent of (X, Z) .

Conditions (ii)–(iv) apply the common (i.e., population-level) distribution of the subjects, and (v) follows from (ii)–(iv).

We now reweight to π to the probability $\tilde{\pi}$:

$$\begin{aligned} \frac{d\tilde{\pi}}{d\pi} &= \frac{c}{p(Z)} \text{ on } \{X = 1\} \\ &= \frac{c}{1 - p(Z)} \text{ on } \{X = 0\} \end{aligned}$$

As Lemma 1 shows, c must be $1/2$ in order for $\tilde{\pi}$ to be a probability; properties (i)–(ii) and (iv)–(v) are preserved, but (iii) becomes

$$\tilde{\pi}(X = 1|Z, V) = 1/2 \quad (*)$$

Furthermore, the joint distribution of Z, V is unchanged; so is the relationship between Y and X, Z, V . All that changes is the conditional distribution of X given Z .

Lemma 1. Let X and W be random variables on $(\Omega, \mathcal{F}, \pi)$, with $X = 0$ or 1 while W takes values in a complete separable metric space \mathcal{M} . Suppose $\pi(X = 1|W) = p(W)$ where $0 < p < 1$ is a Borel function on \mathcal{M} . Let

$$\phi = \frac{X}{p(W)} + \frac{1 - X}{1 - p(W)},$$

a finite, positive, \mathcal{F} -measurable function on Ω . Let c be a positive real number. Define the σ -finite measure $\tilde{\pi}$ on (Ω, \mathcal{F}) by

$$\frac{d\tilde{\pi}}{d\pi} = c\phi.$$

Let B be a Borel subset of \mathcal{M} . Then—

- (i) $\tilde{\pi}(X = 1 \& W \in B) = c\pi(W \in B)$.
- (ii) $\tilde{\pi}(X = 0 \& W \in B) = c\pi(W \in B)$.
- (iii) $\tilde{\pi}(\Omega) = 2c$.
- (iv) $\tilde{\pi}$ is a probability measure iff $c = 1/2$.
- (v) If $c = 1/2$, the $\tilde{\pi}$ -distribution of W coincides with the π -distribution.
- (vi) If $c = 1/2$, then $\tilde{\pi}(X = 1|W) = 1/2$.

Proof. Write 1_B for the indicator function of B . This is a Borel function on \mathcal{M} . Then

$$\begin{aligned}
\tilde{\pi}(X = 1 \& W \in B) &= \int_{\{X=1\}} 1_B(W) d\tilde{\pi} \\
&= \int_{\{X=1\}} 1_B(W) \frac{d\tilde{\pi}}{d\pi} d\pi \\
&= c \int_{\{X=1\}} \frac{1}{p(W)} 1_B(W) d\pi \\
&= c E_{\pi} \left[\frac{X}{p(W)} 1_B(W) \right] \\
&= c E_{\pi} \left\{ E_{\pi} \left[\frac{X}{p(W)} 1_B(W) \middle| W \right] \right\} \tag{**} \\
&= c E_{\pi} \left\{ \frac{p(W)}{p(W)} 1_B(W) \right\} \\
&= c E_{\pi} \{ 1_B(W) \} \\
&= c \pi(W \in B)
\end{aligned}$$

because $E_{\pi}(X|W) = p(W)$ on the right hand side of (**). This proves (i), and (ii) is similar. Then (iii) and (iv) are immediate: take $B = \mathcal{M}$. Now (v) follows by adding (i) and (ii). Finally, (vi) is immediate from (i). QED

Discussion. π describes the original, unweighted world; $\tilde{\pi}$ describes the weighted world. X is treatment status, while $W = (Z, V)$ is the vector of covariates and latents used to construct the response Y , which is computed from X and W in the weighted world using the same formula as in the unweighted world.

Conclusion (v) of the lemma shows that Z and V are independent in the weighted world; (vi) proves (*), and hence the independence of V from (X, Z) . We still have $Y = \Phi(X, Z, V)$, at least almost surely, because $\tilde{\pi} \equiv \pi$.

To be clearer (but fussier), we should start with (X, Z, V, Y) defined on some probability triple $(\Omega, \mathcal{F}, \pi)$, impose conditions (ii)–(v), then define $\tilde{\pi}$ and prove the claims about it. After that, we could introduce IID copies of (X, Z, V, Y) . Each copy would be reweighted. For instance, we could simply take Cartesian products of the basic triple with itself. The unweighted world corresponds to $(\Omega, \mathcal{F}, \pi)^{\mathbb{Z}}$ and the weighted world is $(\Omega, \mathcal{F}, \tilde{\pi})^{\mathbb{Z}}$, where \mathbb{Z} is the sequence of positive integers.

NB. The sample is blown up to population level using the weights, and sampling error is ignored. This is a one-period model, but the argument generalizes to several periods, as we discuss next.

Two periods

The setup is the same, except there are treatment variables X_1 and X_2 for each the two periods, with $\pi(X_1 = 1|W) = p_1(W)$ and $\pi(X_2 = 1|X_1, W) = p_2(X_1, W)$, these functions being positive and less than 1. Let

$$\phi = \frac{1}{p_1(W)} \times \frac{1}{p_2(1, W)} \text{ on } \{X_1 = 1 \& X_2 = 1\}$$

$$\begin{aligned}
&= \frac{1}{p_1(W)} \times \frac{1}{1 - p_2(1, W)} \text{ on } \{X_1 = 1 \& X_2 = 0\} \\
&= \frac{1}{1 - p_1(W)} \times \frac{1}{p_2(0, W)} \text{ on } \{X_1 = 0 \& X_2 = 1\} \\
&= \frac{1}{1 - p_1(W)} \times \frac{1}{1 - p_2(0, W)} \text{ on } \{X_1 = 0 \& X_2 = 0\}
\end{aligned}$$

and let

$$\frac{d\tilde{\pi}}{d\pi} = c\phi.$$

As before, $\tilde{\pi}(X_1 = x_1 \& X_2 = x_2 \& W \in B) = c\pi(W \in B)$. For example, take $x_1 = x_2 = 1$. To simplify the analog of (***) in the proof, we would compute

$$\begin{aligned}
E_{\tilde{\pi}}\left[\frac{X_1 X_2 1_B(W)}{p_1(W)p_2(1, W)} \mid W\right] &= \frac{1_B(W)}{p_1(W)p_2(1, W)} \pi(X_1 = 1 \& X_2 = 1 \mid W) \\
&= \frac{1_B(W)}{p_1(W)p_2(1, W)} \pi(X_1 = 1 \mid W)\pi(X_2 = 1 \mid X_1 = 1, W) \\
&= \frac{1_B(W)}{p_1(W)p_2(1, W)} p_1(W)p_2(1, W) \\
&= 1_B(W).
\end{aligned}$$

Thus, $c = 1/4$ if $\tilde{\pi}$ is to be a probability, and the argument proceeds as before. In the weighted world, i.e., relative to $\tilde{\pi}$ with $c = 1/4$,

- the distribution of W is unchanged,
- X_1, X_2 , and W are independent,
- X_1 and X_2 are each 0 or 1 with probability 1/2.

Here, W represents the initial covariates, as well as the latents used to update covariates, select treatments, and compute responses. The responses Y_1, Y_2 would be computed from treatment variables and latents using the same formulas in the weighted and unweighted worlds, covariates would be updated the same way, etc. The extension to n periods is straightforward.

Example. In Simulation #1 of Freedman and Berk (2008), let $Z_2 = \alpha + \beta Z_1 + \delta$, where δ is random, mean 0, independent of Z_1 . If you omit $c_2 Z_2$ and run a weighted regression of Y on X and Z_1 , then \hat{a} estimates $a + c_2 \alpha$. Given the parameter values in the simulation, namely, $\beta = 1/2$ and $\alpha = 3/4$, the estimand is 2.5, in accordance with the simulation results in Table 1 of that paper.

Reference

D. A. Freedman and R. A. Berk. "Weighting regressions by propensity scores." In press, *Evaluation Review*, vol. 32 (2008). <http://www.stat.berkeley.edu/census/weight.pdf>